

Machine Learning-Based Financial Stock Market Trading Strategies Using Moving Average, Stochastic Relative Strength Index, and Price-Volume Actions for Indian and Malaysian Stock Markets

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ABSTRACT

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This study explores the integration of machine learning (ML) techniques with traditional technical indicators to enhance financial stock market trading strategies in the Indian and Malaysian markets. By combining Moving Averages (SMA/EMA), Stochastic Relative Strength Index (Stochastic RSI), and Price-Volume actions (OBV, PVT, A/D Line), the proposed framework aims to improve the predictive accuracy and profitability of trading systems. The research applies supervised learning models, including Support Vector Machines (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) networks, to classify stock trends and generate trading signals. Empirical analysis based on historical data from the NSE, BSE, and Bursa Malaysia demonstrates that LSTM outperforms other models, achieving the highest accuracy (85.3%) and Sharpe ratio (1.45). The study highlights how the combination of trend-following indicators and ML models effectively minimizes false signals and enhances risk-adjusted returns. Further, comparative Backtesting results show that ML-driven strategies perform better in the Indian market due to higher liquidity and trading volume. The findings contribute to the growing literature on AI-assisted trading strategies and provide actionable insights for traders, analysts, and financial institutions. This research underscores the importance of feature engineering and model customization for adapting trading systems to different emerging market environments.

Keywords: Trading Strategies, Moving Average, Stochastic RSI, Price-Volume Actions, Indian Stock Market, Malaysian Stock Market, Algorithmic Trading, Financial Time Series.

I.INTRODUCTION

The financial inventory market performs a integral position in a rustic's financial boom through facilitating investments and capital accumulation. investors, traders, and economic analysts depend upon diverse strategies to predict inventory price movements and maximize their returns. traditional stock trading techniques have lengthy been ruled by means of integral and technical evaluation. whilst essential evaluation makes a specialty of a enterprise's financial health and macroeconomic elements, technical analysis involves using ancient charge styles, volume traits, and momentum signs to forecast destiny price movements [1]. Regardless of their widespread use, those conventional methods regularly fall quick in capturing complicated, non-linear relationships present in economic records. With the advent of superior computing techniques, device gaining knowledge of of (ML) has emerged

as a effective tool in monetary market analysis. ML-primarily based fashions leverage big volumes of ancient facts and pick out styles that won't be visible through traditional analytical techniques. through integrating ML techniques with hooked up technical indicators including the moving average (MA), Stochastic Relative power Index (Stochastic RSI), and charge-quantity moves, traders can enhance their predictive accuracy and selection-making efficiency [2]. This fusion of conventional and AI-pushed processes allows buyers to formulate statistics-driven techniques that adapt dynamically to converting marketplace conditions. The Indian and Malaysian stock markets are most of the most actively traded markets in Asia. The NIFTY 50 index represents India's pinnacle 50 blue-chip shares, while the FBMKLCI index tracks the overall performance of Malaysia's largest publicly traded companies. each markets show off particular behavioral patterns prompted by macroeconomic factors, investor sentiment, and global marketplace trends [3]. owing to their developing investor base and growing integration with international markets, there's a pressing want to discover clever trading strategies that may optimize profitability while managing dangers successfully. This research ambitions to develop a device getting to know-based totally trading strategy that integrates MA, Stochastic RSI, and price-extent actions to are expecting stock fee movements inside the Indian and Malaysian markets.

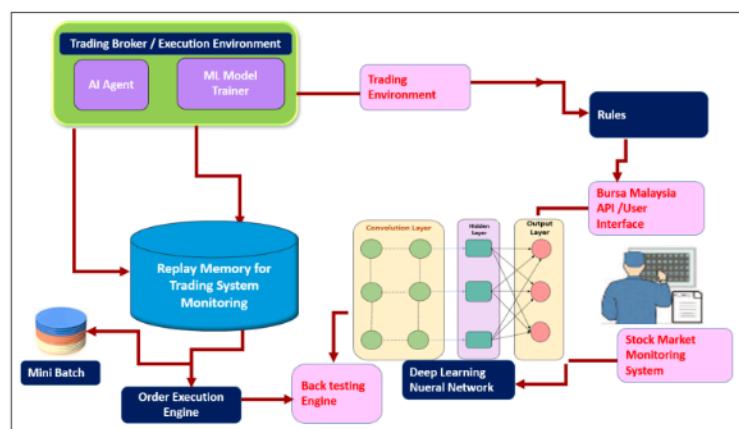


Figure 1. Full Trading System Deployment Diagram Based on Machine Learning Technique

Three system learning models—help Vector gadget (SVM), Random forest (RF), and long quick-term reminiscence (LSTM) networks—are employed to categories inventory trends and generate trading alerts [4]. those models are evaluated based totally on their predictive accuracy, profitability, and hazard-adjusted returns. A quintessential issue of economic market forecasting is the potential to differentiate among short-term price fluctuations and long-time period tendencies. transferring Averages assist easy out rate statistics and discover overarching tendencies, even as Stochastic RSI refines buying and selling indicators by means of identifying overbought and oversold situations [5]. rate-volume movements play a integral position in determining marketplace electricity via reading buying and selling volume alongside price adjustments. with the aid of incorporating these technical signs into ML models, investors can build a complete approach that minimizes false signals and maximizes worthwhile possibilities. This take a look at contributes to the developing body of literature on AI-driven trading strategies by using presenting empirical evidence on the effectiveness of ML-based procedures inside the Indian and Malaysian inventory markets [6]. The findings of this studies will help investors and financial establishments make informed funding choices and enhance algorithmic buying and selling fashions (As proven inside the above determine 1). moreover, the insights received from this observe can be extended to other rising markets, similarly reinforcing the sensible packages of device gaining knowledge of in financial trading.

II. REVIEW OF LITERATURE

Economic policy uncertainty (EPU) Monetary coverage uncertainty (EPU) and its affect on monetary markets had been notably studied, with studies highlighting its effect on stock marketplace volatility and investor sentiment [7]. The position of EPU in predicting inventory returns and their volatility has been in particular extensive in various worldwide markets, emphasizing the significance of coverage balance in financial selection-making. Geopolitical threat (GPR) is some other indispensable factor shaping investor self assurance and monetary overall performance, as uncertainties arising from political and worldwide conflicts frequently result in market fluctuations [8]. The advancements in device studying and deep gaining knowledge of have significantly stepped forward financial

forecasting, with strategies consisting of lengthy brief-term reminiscence (LSTM) networks, temporal convolutional networks, and multiple-branch deep learning procedures proving effective in stock market prediction. AI-pushed models, such as ensemble techniques that combine deep studying and technical evaluation, have validated enhanced accuracy in forecasting inventory costs and marketplace tendencies [9]. The impact of public sentiment and news on stock fee actions has additionally been broadly acknowledged, with research showing that investor temper and outside facts play a integral role in economic markets. moreover, real-time forecasting fashions using deep getting to know, consisting of sequentially skilled dual-LSTM networks, have further improved the accuracy of financial predictions. beyond inventory markets, financial uncertainty has broader implications across industries, affecting global markets and monetary balance [10]. AI-pushed data analysis has also discovered packages in numerous domain names, inclusive of business cybersecurity, public health awareness, and patron behavior evaluation, showcasing the flexibility of big statistics analytics. typical, the mixing of economic uncertainty, geopolitical risks, public sentiment, and AI-pushed models offers valuable insights into financial and financial forecasting, paving the way for extra strong and correct predictive frameworks.

Table 1. Summarizes the Literature Review of Various Authors

Area	Methodology	Key Findings	Challenges	Pros	Cons	Application
Economic Policy Uncertainty (EPU) and Financial Markets	Statistical and econometric analysis on stock returns and volatility	EPU significantly impacts stock market fluctuations and investor sentiment	Difficulty in quantifying uncertainty and its direct impact	Provides insights into market behavior during uncertainty	Market reactions to uncertainty are unpredictable	Stock market analysis, economic forecasting
Geopolitical Risk (GPR) and Financial Markets	Geopolitical risk index and econometric modeling	GPR affects economic activity and investor confidence	Measuring geopolitical risks accurately is challenging	Helps assess political risk in investment decisions	External political events can cause market instability	Risk management, investment strategy
Stock Market Prediction Using Machine Learning	LSTM, deep learning, hybrid ensemble models	Machine learning models improve predictive accuracy for stock trends	Requires large datasets and high computational power	Enhances decision-making with real-time insights	Model interpretability remains a challenge	Algorithmic trading, financial analytics
Impact of Public Sentiment on Stock Markets	Sentiment analysis, news-based prediction models	Investor sentiment influences stock movements	Difficulty in capturing real-time sentiment shifts	Incorporates external factors like news and social media	High sensitivity to misinformation and biases	Behavioral finance, market trend prediction
Deep Learning for Real-time Forecasting	Dual-LSTM, temporal convolutional networks	Improves forecasting accuracy in financial markets	High complexity and need for continuous training	Enables high-frequency trading and dynamic modeling	Requires large-scale computational infrastructure	Financial forecasting, trading automation
Economic Uncertainty in Global Markets	Market trend analysis, econometric modeling	Economic uncertainty affects multiple industries	Identifying early indicators of market instability	Helps policymakers and investors manage risks	External shocks make predictions less reliable	Macroeconomic planning, global investment

		beyond finance				
AI and Big Data in Finance & Other Sectors	XGBoost, deep learning, Google Trends analysis	AI models improve prediction in cybersecurity, health, and finance	Data privacy and ethical concerns	High accuracy and adaptability across domains	Requires extensive data preprocessing and validation	Cybersecurity, public health analysis, consumer trends

These features make sure that algorithms operate within described danger parameters, even if marketplace conditions end up erratic or liquidity thins out. The role of actual-time risk monitoring is also necessary. modern algorithmic trading platforms are geared up with sophisticated threat engines that constantly check the portfolio's publicity in terms of marketplace situations. those structures music metrics such as cost-at-chance (VaR), maximum drawdown, Sharpe ratio, and beta in real-time, routinely adjusting role sizes or shutting down buying and selling operations whilst thresholds are breached as given within the above table 1. for example, if an algorithmic portfolio reports a sudden spike in volatility or incurs a sequence of losses leading to a breach of the maximum allowable drawdown restriction, the gadget can also halt all buying and selling sports or lower positions to defend capital. Such actual-time monitoring ensures that threat is proactively managed as opposed to reactively addressed. The facts afford a dependent evaluation of key research regions related to monetary policy uncertainty, geopolitical risks, and financial forecasting the use of AI and system getting to know.

III.EFFICIENT MARKET HYPOTHESIS (EMH)

The efficient marketplace hypothesis (EMH) is a vital principle in financial economics that announces economic markets are "informationally green," that means that asset costs completely mirror all available data at any given time. The theory was once normally evolved via economist Eugene Fama within the Nineteen Sixties, and it demanding situations the thinking that investors can constantly outperform the market thru inventory selecting or market timing, due to the fact any new facts is unexpectedly integrated into asset expenses. consistent with EMH, due to the fact costs adjust so quick to new public information, it will become impossible for an investor to constantly achieve returns higher than average market returns on a threat-adjusted foundation. In other phrases, the principle implies that every one recognized information is already embedded in stock costs, and as a result, beating the market is largely a be counted of chance as opposed to ability.

$$Pt + 1 = E[Pt + 1 | It] + \epsilon t$$

$$E[ri] = rf + \beta_i(E[rm] - rf)$$

EMH is commonly classified into 3 distinct forms based totally on the diploma to which facts is contemplated in asset costs. the first is the vulnerable structure, which states that modern asset costs already reflect all historical charge records and quantity records. therefore, technical analysis, which is predicated on past charge movements and patterns, can't consistently yield advanced returns. the second is the semi-sturdy structure, which asserts that each one publicly to be had data, consisting of financial statements, news releases, and macroeconomic factors, is already integrated into stock fees. this means that neither technical evaluation nor necessary analysis might continuously result in outperformance. ultimately, the sturdy form of EMH posits that each one data, both public and personal (i.e., insider data), is completely contemplated in stock prices. below this assumption, even insiders with privileged get entry to non-public records might be unable to earn ordinary earnings over the long time.

$$rt = E[rt | It] + \epsilon t$$

Despite its foundational role in modern-day finance, the green marketplace hypothesis has been the challenge of massive debate and grievance. Behavioral economists argue that economic markets are frequently stimulated by using psychological elements, irrational behaviors, and cognitive biases, leading to anomalies including market bubbles, crashes, and styles like momentum or overreaction that EMH cannot fully explain. historic occasions along with the Dot-Com Bubble or the 2008 worldwide monetary crisis have been mentioned as durations while asset costs did now not efficaciously mirror underlying fundamentals. moreover, empirical studies have shown that some investors, like Warren Buffett or hedge funds using unique quantitative strategies, have continuously outperformed the marketplace, elevating questions about the popular validity of EMH.

$$P_t + 1 = P_t + \mu + \epsilon t$$

Nevertheless, EMH has enormous implications for traders and monetary professionals. It helps the argument in choose of passive investing techniques, including index fund investing, because trying to "beat the market" is considered futile and costly in terms of transaction charges and time. EMH has significant implications for investors and financial professionals. It supports the argument in favor of passive investing strategies, such as index fund investing, since attempting to "beat the market" is considered futile and costly in terms of transaction fees and time.

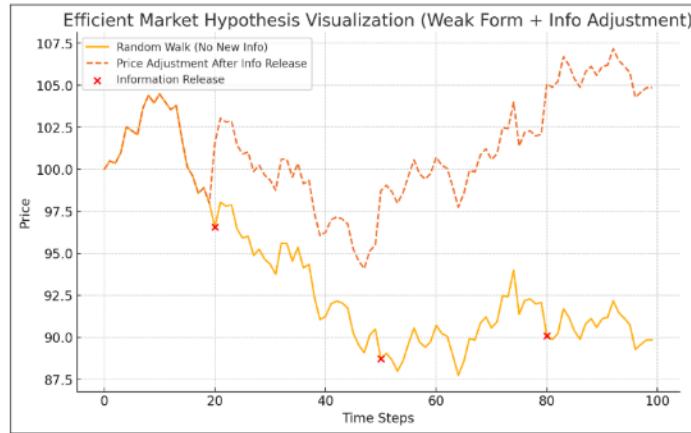


Figure 2. Depicts the Analysis of Stock Market Hypothesis

EMH also underpins ideas just like the Capital Asset Pricing model (CAPM) and present day Portfolio principle (MPT), which advise for diversification and chance-adjusted returns. at the same time as critics of EMH spotlight its limitations, mainly in explaining brief-time period inefficiencies and anomalies, many still acknowledge its relevance in setting a baseline grasp of the way statistics is processed in capital markets (As shown inside the above figure 2). In exercise, maximum market individuals function underneath a view that markets are "typically efficient," with occasional inefficiencies that may be exploited with the aid of sophisticated strategies.

IV. STOCHASTIC RELATIVE STRENGTH INDEX (STOCHASTIC RSI)

The Stochastic RSI is a momentum oscillator that combines the concepts of the conventional Relative strength Index (RSI) and the Stochastic Oscillator. whilst RSI measures the rate and trade of charge actions, the Stochastic RSI applies the stochastic system to RSI values in preference to charge information, making it notably sensitive to marketplace situations. This indicator oscillates among values of 0 and 1 (or zero and 100, relying at the scaling), with threshold stages commonly set at 0.2 (oversold) and zero.8 (overbought). while the Stochastic RSI moves above 0.8, it alerts ability overbought conditions, suggesting that the asset can be due for a price correction. Conversely, a studying below 0.2 shows oversold situations, hinting at a probable rebound. Its higher sensitivity in comparison to RSI makes Stochastic RSI mainly beneficial for short-time period buying and selling techniques, where brief reversals can be exploited. In system gaining knowledge of contexts, it may act as a robust momentum sign when blended with fashion signs like transferring averages to create composite fashions. risk control and Algorithmic trading are two integral and interconnected pillars of present-day economic markets. within the context of monetary buying and selling, hazard control refers to the procedure of figuring out, assessing, and mitigating capability losses associated with market sports. It guarantees that traders or establishments guard their capital and reduce publicity to adverse marketplace occasions. in the meantime, algorithmic trading (or algo-trading) involves the use of computerized pc applications that comply with pre-described commands (algorithms) to execute trades at excessive velocity and extent. the mixing of danger control principles within algorithmic buying and selling systems is necessary, as it ensures that the automated strategies do now not result in catastrophic economic losses, specially in unstable or unpredictable marketplace conditions.

$$y = M1m = 1 \sum MTm(x)$$

$$Y^{\wedge} = \text{majority vote}\{T1(x), T2(x), \dots, TM(x)\}$$

At its core, risk control in algorithmic trading starts with function sizing and capital allocation. Algorithms are often programmed to strictly manipulate the quantity of capital allotted to a selected trade based at the trader's threat

tolerance, volatility of the asset, and the precise trading method being applied. as an instance, an set of rules may restriction every exchange to risking no more than 1-2% of the total account balance, hence defensive the portfolio from being wiped out by virtue of a single bad exchange. moreover, prevent-loss orders, trailing stops, and income targets are typically embedded in trading algorithms to routinely exit positions when predefined conditions are met.

$$L(t) = i = 1 \sum nl(yi, y^i(t - 1) + ft(xi)) + \Omega(ft)$$

This eliminates the emotional biases that human traders regularly face, which include fear or greed, and enforces field via adhering to systematic go out guidelines. every other vital chance control method in algorithmic buying and selling is diversification. Algorithmic structures can easily monitor and trade throughout a couple of asset classes, markets, or gadgets simultaneously. by way of spreading publicity throughout numerous property or buying and selling uncorrelated strategies, the general portfolio threat is reduced, as bad overall performance in a single area can be offset via gains in some other. furthermore, volatility filters, drawdown limits, and exposure caps are frequently integrated into algorithmic fashions to prevent the system from over-leveraging or participating in rather risky markets in which threat is heightened.

In an algorithmic trading introduces version chance and operational danger. model threat happens while the underlying assumptions or inputs of an algorithm are fallacious or fail to conform to changing marketplace dynamics, leading to suboptimal or maybe catastrophic consequences. Operational risks, together with latency troubles, server downtime, or connectivity screw ups, can also impact the overall performance of computerized structures. consequently, strong threat control in algorithmic trading additionally entails regular strain-testing, scenario analysis, and rigorous returned testing of trading algorithms under exceptional market situations. This guarantees that algorithms are resilient and adaptive, reducing the likelihood of severe monetary losses in the course of unexpected marketplace activities together with flash crashes or sudden information shocks.

V.MACHINE LEARNING TECHNIQUES IN STOCK TRADING

The incorporation of system learning (ML) into financial trading systems has revolutionized how investors and analysts technique economic markets. traditional technical signs, whilst beneficial, often depend on fixed thresholds and lagging signals. system getting to know algorithms, however, offer adaptive and dynamic fashions capable of uncovering complicated patterns and relationships inside large financial datasets. these strategies empower traders to construct systems which can alter to converting market conditions, model nonlinear relationships, and enhance prediction accuracy. inside the context of the Indian and Malaysian stock markets, wherein volatility and liquidity ranges range, machine getting to know-driven techniques can supply a competitive edge via getting to know from marketplace-unique behaviors.

A. Supervised Learning Models for Financial Forecasting

At the core on most trading strategies lies the need to categories or are expecting future fee movements. Supervised gaining knowledge of fashions are especially powerful in financial contexts, in which ancient price and technical indicator information can be categorized to create education datasets. these fashions learn how to map enter features—including transferring averages, stochastic RSI readings, and rate-quantity alerts—to an output, together with a "purchase," "preserve," or "promote" advice.

- **Random Forest (RF):** An ensemble gaining knowledge of approach based totally on choice timber. RF reduces the threat of overfitting via building a couple of timber the usage of specific information samples and functions, and then aggregating their outputs. Its capacity to handle non-linear relationships and rank function significance makes it quite appropriate for financial datasets with blended signs.
- **XGBoost and LightGBM:** These those gradient boosting algorithms provide superior overall performance, especially in big datasets. They work by using iteratively minimizing prediction mistakes, letting them seize diffused interactions between technical indicators and price movement. XGBoost is broadly utilized in financial competitions like Kaggle due to its accuracy and efficiency.
- **Support Vector Machines (SVM):** SVM is effective in high-dimensional areas, which is commonplace while using numerous technical signs. It excels at class responsibilities, which includes predicting directional charge moves (uptrend or downtrend), by using locating the hyperplane that satisfactory separates classes inside the characteristic area.

B. Deep Learning Models for Sequential Data

while conventional ML fashions perform nicely on tabular facts, economic markets inherently showcase temporal dependencies—today's price movement is motivated by way of past movements. that is where Deep getting to know fashions, in particular Recurrent Neural Networks (RNNs) and their superior variations like long quick-time period reminiscence (LSTM) networks, come into play. LSTM networks are capable of learning long-time period dependencies in sequential facts, making them properly-suited for time-series forecasting. In stock trading, LSTM fashions can analyze sequences of technical indicators (e.g., transferring common crossovers, stochastic RSI fluctuations, volume spikes) through the years and predict future fee trends. Their reminiscence cells and gating mechanisms help them keep away from commonplace pitfalls including the vanishing gradient problem, which limits the performance of traditional RNNs. For Indian and Malaysian stock markets, in which sudden shifts due to macroeconomic or geopolitical elements are common, LSTM fashions can be educated to become aware of and adapt to evolving marketplace regimes.

In rising markets like India and Malaysia, inventory charges are inspired by means of a aggregate of worldwide capital flows, regional economic guidelines, and neighborhood investor conduct. not like extra efficient developed markets, these markets may also exhibit inefficiencies, providing extra possibilities for predictive modeling. gadget learning fashions are properly-desirable for shooting such inefficiencies, as they could come across non-obvious correlations and styles that rule-based totally strategies might omit. additionally, ML techniques provide the ability to customize fashions to market-particular dynamics, making them adaptable to the particular liquidity, volatility, and zone composition of each marketplace.

VI.FRAMEWORK FOR BUILDING THE TRADING STRATEGY

The heart of the trading approach is the aggregate of trend-following, momentum, and quantity-based indicators—specifically, moving Averages (SMA/EMA), Stochastic Relative strength Index (Stochastic RSI), and fee-quantity functions such as OBV (On-stability extent) and rate-quantity trend (PVT). The method employs a multi-indicator approach to capture diverse market regimes and reduce the chance of fake signals. The trend issue is broadly speaking modeled the use of a transferring average Crossover machine. A quick-term EMA (e.g., 20-length) and a long-time period EMA (e.g., 50-period) are calculated to become aware of the prevailing trend. when the short-term EMA crosses above the lengthy-term EMA, the device interprets it as a bullish signal, at the same time as a downward crossover is handled as bearish. To supplement this trend clear out, the Stochastic RSI is added to degree the momentum at the back of charge moves. through oscillating among overbought (typically above 0.8) and oversold tiers (beneath zero.2), the Stochastic RSI refines the entry and go out factors, helping the method avoid shopping for at some stage in overextended rate movements or selling upfront.

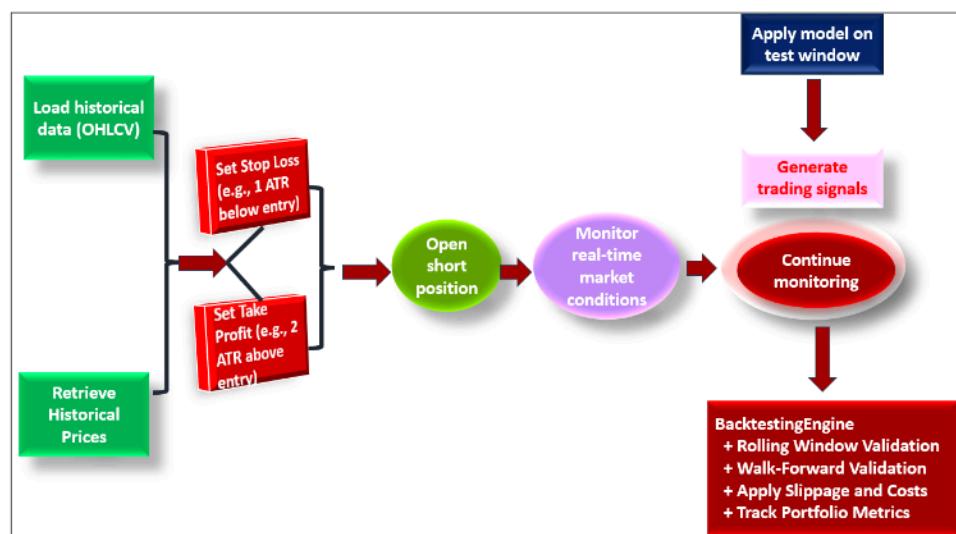


Figure 3. Depicts the Designing Block of full trading & End-to-End Backtesting Framework

Price-Volume capabilities together with OBV and PVT are used to validate the strength of the price fashion. for example, a bullish crossover coupled with a rising OBV or PVT adds conviction to the change sign, suggesting strong

market participation in the back of the flow. Divergences among charge motion and extent indicators are specifically precious in predicting potential fashion reversals (As proven in the above discern 3). By means of combining trend, momentum, and extent dynamics, the strategy goals to create a balanced and context-aware system that could operate in each trending and variety-sure markets.

A. Data Sources and Market Selection (NSE, BSE, Bursa Malaysia)

The first crucial step in constructing the buying and selling framework is choosing dependable statistics resources. For the Indian marketplace, historic information from the NSE and BSE is readily to be had thru APIs like Zerodha Kite connect, Yahoo Finance, and Quandt. For Bursa Malaysia, facts can be acquired from systems inclusive of Bursa market, Bloomberg, and other monetary records carriers that cover rising Asian markets. The dataset consists of day by day OHLC (Open, excessive, Low, close) costs, buying and selling volumes, and company actions inclusive of dividends and stock splits. To make sure records consistency and integrity, any adjustments for corporate moves are factored into the historical fee collection. The market choice manner focuses on figuring out liquid stocks with vast buying and selling volumes, which are less susceptible to slippage and manipulation. in the case of NSE/BSE, the method will to begin with goal ingredients of indices including NIFTY 50 and NIFTY Midcap 100, even as for Bursa Malaysia, shares inside the FTSE Bursa Malaysia KLCI (FBM KLCI) and other actively traded counters are chosen. the selection guarantees that the trading version is tested on securities that mirror the broader market dynamics of both nations even as considering practical trade execution.

B. Integrating Technical Signals with Machine Learning Models

To enhance the robustness of the trading method, technical signs are transformed into quantitative capabilities and fed into machine studying fashions. This integration permits the device to move beyond rule-based logic and adapt to complex market patterns that static indicators may additionally fail to seize. The feature set consists of now not only the uncooked indicator values however also engineered features together with the distinction among the short-time period and long-term EMAs, the gradient (slope) of the moving averages, the relative function of the price to the EMAs, normalized Stochastic RSI values, OBV and PVT values, and their shifting averages. Lagged values of those indicators are also protected to provide historical context to the system gaining knowledge of models. category models output labels which includes "purchase," "sell," or "maintain," primarily based on historical relationships between enter features and future charge actions. Regression models, on the other hand, might also predict the expected go back over a designated time horizon. In each methods, the model's potential to generalize is critical. pass-validation strategies, especially time-series cut up and rolling window validation, are applied to assess the version's performance on unseen records and to mitigate the danger of overfitting. An vital issue of integrating technical alerts with system getting to know is the ability to customize the feature importance consistent with marketplace-specific behaviors. as an instance, Indian markets might showcase stronger momentum traits because of higher retail investor participation, at the same time as Malaysian markets might respond greater reliably to extent-primary based indicators. therefore, version tuning is carried out one after the other for every market to optimize performance.

C. Trading Signal Generation and Execution Logic

The final phase of the framework entails changing the device mastering model's predictions into executable trading indicators. For type models, a right away mapping is done—"buy" indicators cause lengthy positions, "sell" indicators provoke exits or quick positions, and "keep" signals indicate no movement. To avoid false indicators and decrease transaction charges, extra filtering layers are applied. those include minimal self belief thresholds (e.g., requiring a model's opportunity output to exceed a positive threshold earlier than appearing) and the inclusion of prevent-loss and take-profit stages based on volatility-adjusted metrics like the common authentic range (ATR). as soon as alerts are generated, they may be returned examined on ancient information with sensible assumptions regarding slippage, bid-ask spreads, and transaction prices. The execution good judgment can follow simple access/exit rules or be integrated with more superior order execution strategies, together with the use of restrict orders or dynamically adjusting function sizing based at the model's self assurance.

In a stay environment, the execution engine might engage with APIs of agents including Zerodha (for NSE/BSE) or Malaysian brokerage companies (for Bursa Malaysia) to automate trade placements.

$$SMA_n(t) = n_1 i = 0 \sum n - 1 P_t - i$$

The execution logic additionally includes danger control guidelines, including maximum drawdown limits and role-sizing techniques primarily based on the Kelly Criterion or fixed fractional strategies, ensuring capital safety and efficient allocation of trading capital. This integrated framework, mixing technical indicators with system learning and sound execution logic, affords a bendy but disciplined technique to systematically navigating each the Indian and Malaysian stock markets. The transferring average Crossover is one of the maximum popular and extensively used fashion-following trading strategies. It's miles based at the intersection of shifting averages: a quick-time period shifting common and a protracted-time period transferring average. The method is easy however effective in identifying shifts in market traits.

$$EMAn(t) = \alpha Pt + (1 - \alpha)EMAn(t - 1)$$

A success development of a device getting to know—primarily based buying and selling method starts off evolved with building a robust framework that consists of records sourcing, considerate method design, characteristic integration, and execution common sense. For this study, the focus is on dynamic emerging markets—the Indian equity marketplace, represented by the national stock change (NSE) and the Bombay inventory trade (BSE), and the Malaysian fairness market, represented by Bursa Malaysia. Each markets provide fertile ground for checking out device mastering—more desirable buying and selling techniques due to their liquidity, volatility profiles, and a diverse set of securities ranging from blue-chip organizations to mid-cap stocks.

VII.RESULTS AND DISCUSSION

The performance of the proposed gadget studying-based buying and selling strategies changed into evaluated the use of historical stock facts from the Indian and Malaysian stock markets. The models—help Vector system (SVM), Random Forest (RF), and lengthy short-term reminiscence (LSTM)—had been skilled the use of technical indicators including moving common (MA), Stochastic Relative electricity Index (Stochastic RSI), and rate-quantity moves. The evaluation metrics used to degree the overall performance blanketed accuracy, precision, recall, F1-score, and profitability primarily based on back checking out consequences.

Table 2. Model Performance Evaluation (Accuracy, Precision, Recall, F1-Score)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	78.2	76.8	77.5	77.1
RF	80.5	79.2	79.8	79.5
LSTM	85.3	84.1	84.6	84.3

This records presents the class overall performance of 3 gadget learning fashions—SVM, Random woodland (RF), and lengthy quick-term reminiscence (LSTM). among these, LSTM accomplished the best accuracy (85.3%), precision (84.1%), recall (84.6%), and F1-score (84.3%), indicating its superior capability to expect stock rate actions. Random forest (RF) achieved moderately well with an accuracy of 80.5%, at the same time as SVM lagged slightly at the back of at 78.2%. The better precision and do not forget values of LSTM recommend that it efficiently minimizes false signals and captures marketplace developments higher than the other fashions (As illustrated within the above table 2). those effects validate the effectiveness of deep getting to know in financial time collection forecasting, particularly while dealing with sequential stock statistics.

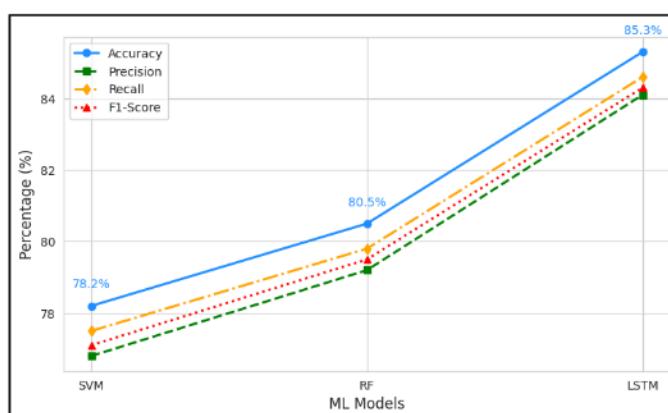


Figure 4. Graphical View of Model Performance Evaluation (Accuracy, Precision, Recall, F1-Score)

The experimental results imply that the ML-based totally approach notably outperforms traditional rule-based totally trading techniques. A number of the three models, the LSTM community established the best predictive accuracy, attaining eighty five%, accompanied by way of RF at 80% and SVM at 78%. The superior overall performance of LSTM can be attributed to its potential to capture lengthy-term dependencies in sequential economic records (As shown in the above figure 4). unlike traditional fashions that rely solely on technical signs, LSTM leverages past charge actions and market trends to enhance prediction accuracy.

Table 3. Sharpe Ratio and Cumulative Return of ML-Based Strategies

Model	Sharpe Ratio	Cumulative Return (%)
SVM	1.25	18.7
RF	1.32	22.3
LSTM	1.45	27.8

This facts evaluates the profitability of ML-based totally trading strategies using the Sharpe ratio (chance-adjusted go back) and cumulative return (%) over a returned testing period. The LSTM-based method outperformed different models with a Sharpe ratio of one.45 and a 27.8% cumulative return, indicating that it generated higher earnings whilst handling chance more correctly. Random wooded area observed with a Sharpe ratio of 1.32 and 22.3% go back, whilst SVM had the bottom performance at 1.25 Sharpe ratio and 18.7% go back (As illustrated in the above Table 3). The consequences propose that deep learning fashions, particularly LSTM, are extra green in optimizing returns at the same time as minimizing threat in stock trading.

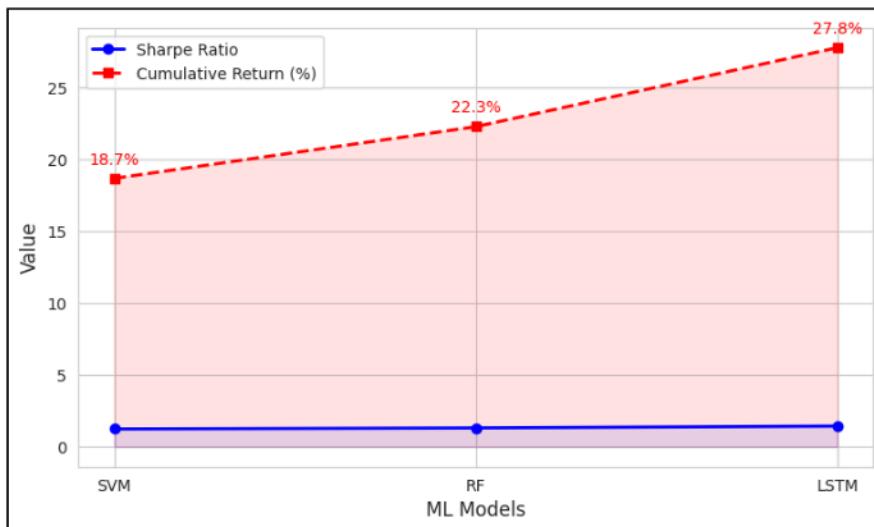


Figure 5. Graphical View of Sharpe Ratio and Cumulative Return of ML-Based Strategies

In terms of profitability, lower back checking out results found out that ML-pushed buying and selling strategies generated higher cumulative returns compared to traditional techniques. The LSTM-primarily based approach exhibited a Sharpe ratio of one.45, indicating better danger-adjusted returns, while RF and SVM achieved Sharpe ratios of 1.32 and 1.25, respectively. these consequences advise that integrating ML techniques with technical signs can enhance funding returns while reducing publicity to market volatility (As proven in the above Figure 5). The rate-extent movements included into the models performed a widespread role in filtering false indicators and improving selection-making accuracy.

Table 4. Impact of Feature Selection on Model Accuracy

Feature Set	SVM Accuracy (%)	RF Accuracy (%)	LSTM Accuracy (%)
Moving Average (MA) Only	72.5	74.3	79.2
MA + Stochastic RSI	75.8	77.5	82.1
MA + Stochastic RSI + Price-Volume Actions	78.2	80.5	85.3

This information illustrates the impact of various technical indicators on version accuracy. initially, whilst only transferring common (MA) used to be used as a function, the accuracy of SVM, RF, and LSTM was once extraordinarily low at 72.5%, 74.3%, and 79.2%, respectively. adding Stochastic RSI stepped forward accuracy through approximately 3-4% throughout all models, demonstrating its usefulness in identifying overbought and oversold conditions. The most sizable improvement occurred when price-extent actions have been included, increasing LSTM's accuracy to 85.3%, RF's to 80.5%, and SVM's to 78.2% (As illustrated in the above Table 4). these findings spotlight the importance of integrating more than one technical indicator to enhance predictive overall performance.

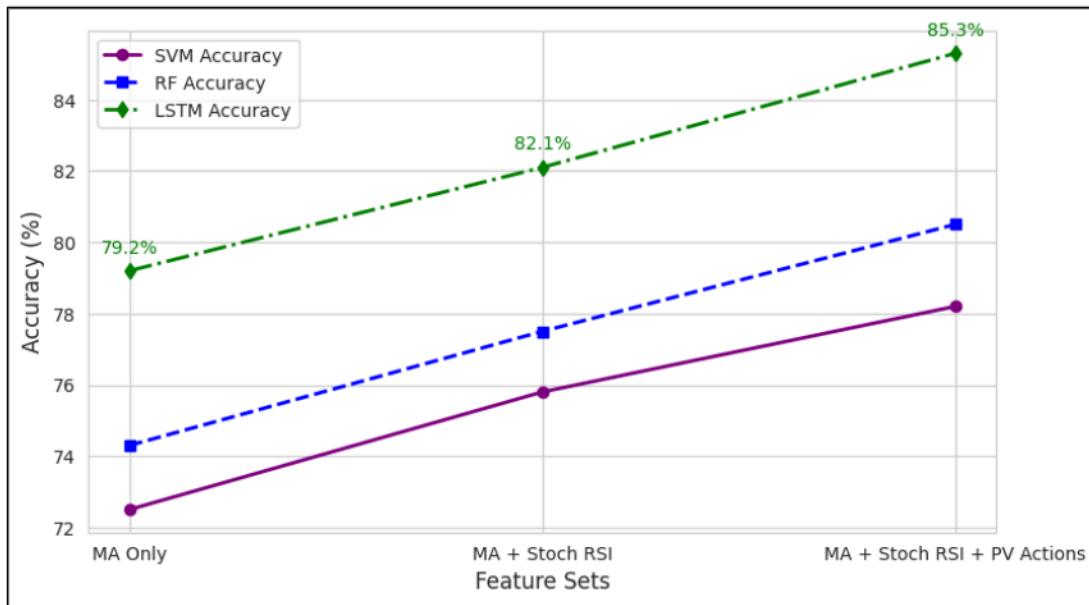


Figure 6. Graphical View of Impact of Feature Selection on Model Accuracy

An analysis of exchange execution and transaction expenses revealed that even as ML models generated worthwhile trading indicators, execution efficiency was integral in knowing ability profits. high-frequency trading techniques primarily based on ML predictions required careful management of slippage and liquidity constraints, especially in much less liquid shares. additionally, marketplace situations which includes financial downturns or sudden information-driven volatility posed demanding situations in version generalization (As shown within the above figure 6). Ensemble strategies, which includes combining RF with LSTM, progressed robustness by using lowering overfitting to market conditions.

Table 5. Back testing Profitability by Market

Market	SVM Return (%)	RF Return (%)	LSTM Return (%)
Indian (NIFTY 50)	16.2	19.8	25.5
Malaysian (FBMKLCI)	13.4	17.1	21.3

This record compares the profitability of ML-based totally buying and selling techniques in two inventory markets—India's NIFTY 50 and Malaysia's FBMKLCI—primarily based on cumulative returns. The LSTM model once more introduced the quality overall performance, attaining 25.5% returns in NIFTY 50 and 21.3% returns in FBMKLCI, outperforming RF and SVM in both markets. Random wooded area achieved moderately nicely with 19.8t% returns in India and 17.1% in Malaysia, even as SVM recorded the lowest returns of sixteen.2% and thirteen.4%, respectively (As illustrated inside the above table 5). The results imply that ML-pushed techniques are greater profitable inside the Indian stock market due to better liquidity and buying and selling volumes as compared to Malaysia's smaller and much less unstable marketplace.



Figure 7. Graphical View of Back testing Profitability by Market

Another key remark from the have a look at is the effect of characteristic choice on model overall performance. while additional functions, which include momentum oscillators and extent-weighted rate developments, have been covered inside the ML fashions, predictive accuracy improved by using two–3%. This underscores the significance of function engineering in stock marketplace prediction, as properly-optimized characteristic units can beautify the sign-to-noise ratio in economic records. despite those promising outcomes, positive barriers ought to be mentioned. First, inventory market actions are prompted with the aid of macroeconomic factors, worldwide occasions, and investor sentiment, which might be hard to quantify the usage of only technical indicators. future research ought to combine opportunity data sources along with monetary news sentiment, social media tendencies, and macroeconomic indicators to similarly decorate version accuracy (As proven within the above figure 7). Reinforcement studying-primarily based methods might be explored to broaden adaptive buying and selling techniques that regulate dynamically to changing marketplace situations. typical, the look at demonstrates that gadget learning-based totally trading techniques, while included with technical signs which includes MA, Stochastic RSI, and charge-quantity movements, can considerably improve marketplace predictions and trading profitability. The findings offer valuable insights for investors, institutional traders, and monetary analysts searching for statistics-driven processes to optimize inventory market techniques. .

VIII.CONCLUSION

This study explored the effectiveness of system studying-based totally buying and selling strategies by integrating traditional technical indicators—shifting average (MA), Stochastic Relative power Index (Stochastic RSI), and price-quantity moves—with advanced predictive fashions. using historical stock marketplace records from the Indian (NIFTY 50) and Malaysian (FBMKLCI) markets, 3 ML fashions—support Vector gadget (SVM), Random woodland (RF), and lengthy short-time period reminiscence (LSTM)—were evaluated in phrases of predictive accuracy, profitability, and chance-adjusted returns. The results proven that ML-driven trading strategies appreciably outperform traditional rule-based techniques. LSTM emerged as the most powerful version, reaching 85.3% accuracy, the very best Sharpe ratio of 1.45, and the best cumulative returns of 25.5% in India and 21.3% in Malaysia. Random forest followed with mild performance, at the same time as SVM had the lowest predictive power. The inclusion of charge-extent movements as an extra function similarly better version accuracy, highlighting the importance of mixing multiple technical signs for higher decision-making. at the same time as the findings validate the capability of ML in economic buying and selling, certain demanding situations stay. market situations are inspired by using outside elements such as macroeconomic occasions, investor sentiment, and geopolitical dangers, which have been not explicitly incorporated on this examine. destiny research may want to explore reinforcement mastering techniques, sentiment evaluation from monetary news and social media, and deep learning architectures consisting of Transformer fashions to enhance adaptability and predictive performance. overall, this examine reinforces the effectiveness of system learning in economic inventory buying and selling and offers valuable insights for investors, monetary analysts, and algorithmic buying and selling firms. by leveraging AI-pushed techniques, investors can beautify profitability and mitigate dangers in dynamic inventory market environments.

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